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Just do it! Combining agent-based travel demand models with queue based-traffic flow models

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Abstract

Proper travel demand models aim to create an equilibrium between expected travel times in the planning phase and simulated travel times after mapping the road traffic on the road network. While agent-based travel demand models (ABM) focus on the trip generation mainly based on pre-calculated travel times, traffic flow models simulate these trips and compute travel times taking into account speed restrictions and road capacities. This leads to deviations between the simulated travel times and the initially expected ones especially during rush hour so that both models are not in equilibrium state. Due to the complexity and limited computational resources, combinations of these two models are often simplified in either one or both parts. In this work we present an iteratively combined simulation model with feedback of travel times. We couple an ABM with a queue-based traffic flow model which simulates the set of trips for each agent. The ABM used adjusts its activity generation, destination choice and mode choice according to the re-calculated travel times resulting in more realistic day plans. The traffic flow model takes the sequential character of the trips into account and propagates the delay to the subsequent trips of each modelled agent, resulting in feasible trips. We show that equilibrium of travel time between these two models can be achieved with a low number of iterations. Our approach is sensitive to new travel times in destination and mode choice and results in trips which are consistent for a whole day for each modelled agent.

Keywords: agent-based modelling, traffic flow, travel demand, dynamic traffic assignment

1. Introduction

Proper travel demand models approach equilibrium between expected travel times in the planning phase and simulated travel times after mapping the road traffic on the road network. The general simulation technique can be divided into two parts: First, the planning phase, where an agent chooses its activities, destinations and mode of

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transports to synthesize a whole day plan of activities. Second, the routing phase, where all trips are mapped on a road network, to simulate travel times with respect to congestions.

During the planning phase activities, destinations and modes of transport are chosen mainly based on expected travel times, which can be initially based on real-life data. Traffic flow models try to route a fixed travel demand through a road network limited by the road network's speeds and capacities. Ideally, the expected travel times meet the simulated ones. Especially during peak hours, however, this is rarely the case. If other parameters like transport costs, employment rate or car availability change, the resulting travel demand from the ABM changes significantly and the traffic flow simulation will deliver different travel times than the ones used during trip computation. The deviations lead to a problem which cannot be solved in one part of the models alone. The deviation of the travel times delays the start and end of the planned activity, which might result in a change of activity, destination or mode of transport. A traffic flow model on its own might propagate the delays of individual trips along all daily activities of an agent to preserve the temporal order of the chain of trips. This leads to feasible trips, but the overall day plan might become completely unrealistic. Had the agent known this during the planning phase, he might have rejected the plan. An ABM reacts to these deviations with a different choice of modes, destinations, or even a different day plan with other activities to make the trips match the used survey data that delivers the daily plans. However, the deviations in travel times are caused by congestions emerging from the trips of all agents. This leads to a paradox, as the ABM would have to know the effects of the results computed by the traffic flow model in advance. This contradiction is generally solved by iterative execution of both models until equilibrium of travel times is reached.

In this work we present an iteratively combined simulation model with feedback of travel times. We show that equilibrium of both models can be reached within a few iterations. Destinations and modes of transport are adjusted to avoid heavily congested areas. The daily activities are not only optimized to be feasible on their own but to maintain a valid day structure with additional constrains like a correct sequence of activities and shared usage of a single car in the household.

The paper is structured as follows: First, we give a brief overview of on related work. Second, we present the research setting. Then we present the simulated results and discussion. We close the work with a conclusion and give an outlook for next tasks we are researching.

2. Related work

Classic 4-step transport models like commercially available programs such as VISUM by PTV or Cube by Citylabs have dominated the marked for traffic simulation, measure assessment and decision making for a long time. However, these models have certain limits, such as hardly achievable consistencies of trip chains or implementation of shared resources such as cars in the same household. ABM solves this issue by modelling the travel demand as the sum of individual trips, but lacks feedback of that change over the day due to a changing demand. To map the generated trips on the simulated infrastructure, dynamic traffic assignment models (DTA) can be used. However, DTA models like MATSim[9] or "Simulation of Urban MObility" (SUMO)[10] alone can only optimize the route and start times of the trips. Choosing the mode of transport, locations or activities is not the main goal of MATSim. SUMO considers trip information as an input.

To adjust the travel demand to the travel times of the road network, ABMs were previously coupled to DTAs[12]. Even a classification of levels of integration is proposed by Pendyala et al. [13]. This classification considers sequentially integrated models as the simplest ones. Those models cannot handle short-time events like network disruptions. Models like SimTRAVEL[14] are more integrated and share routing information between the DTA and the ABM during the generation of the trips to react to network conditions. These dynamically integrated models process all agents chronologically to map the entire traffic at a given time of day. This enables the DTM to propagate delays back to the AMB parallel to the planning phase. Hence, short-term effects like road closures can be modelled appropriately, but the original plan of a person can become unfeasible due to additional time constrains like picking up children from school, visits to the theatre etc., like in real life. But if long-term effects like demographic change or network extensions are modelled, these short-term effects are only of little interest and sequential integration is sufficient.

3. Research setting and methods

Our approach assumes that during the planning phase every person has full knowledge of the network state. Furthermore, the simulated day plans are optimized by using three criteria: First, mode choice in order of the priority of the trip, second, accessibility of locations considering the remaining time budget and third, overall time budget compared to reported time budget. The ABM used in this study is named “Travel-Activity and PAttern Simulation” (TAPAS)[7,8]. Its functional blocks are shown in Fig. 1. It takes every person, also known as agent, from a synthetic population, selects an activity plan, tries to find locations and modes of transport taking into account the actual situation and finally evaluates the day plan for acceptance. The synthetic population used fits the statistical data of the city of Berlin, Germany, in the year 2010. The main parameters for the population can be found in Table 1. The activities are derived from reported day plans from the national household survey called MiD2008[11]. The activity types are education, work, shopping, free time and private matters like going to a mail box. The population is grouped into households consisting of one to five persons. Cars are a shared resource in each household. Each household member represents an agent and is allowed to draw one of the reported day plans. The probability of selecting a day plan is in line with the typical probability of the type of person and the day plan type, which are precalculated[5]. This ensures that persons select activities which fit their socio-demographic circumstances, like part-time work or presence of children. The city structure is divided into 1193 traffic cells, with travel times for walking, cycling, driving a car and using public transport (PT) and capacity-restricted locations for performing different activities. For each person, TAPAS generates a day plan consisting of a list of all performed trips.

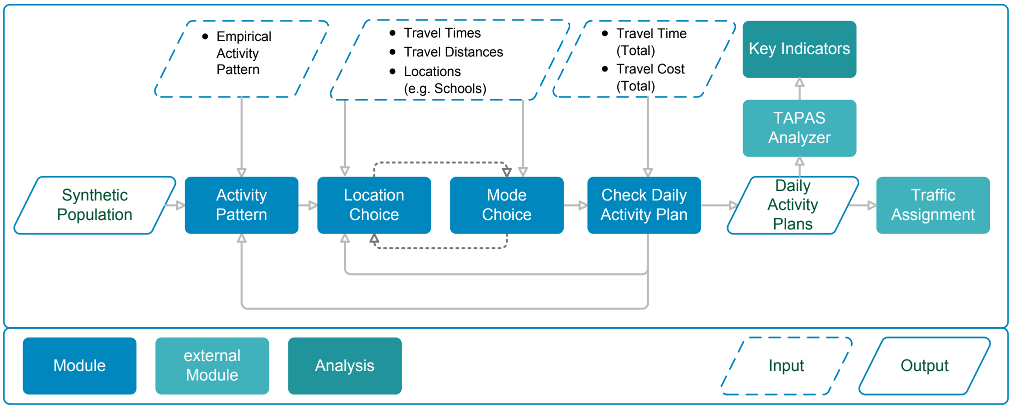

Fig. 1: TAPAS functionality

The choice of a certain mode of transport depends on the travel time, among other things. The initial travel time matrix for car trips is based on an empty net. This matrix shows much faster travel times than the real ones due to the lack of modelling congestions. Therefore, we reduced the average speed of all connections to meet the realistic average car speed. The Berlin household survey called SrV2008[1] reported an average speed for car trips of 23.5 km/h for all trips within Berlin, not counting long-distance trips of more than 70 km. Travel times of walking and cycling are generated by applying the average travelling speed to the net distance of a shortest path routing. Public transport information is derived from publicly available GTFS data from 2013[2].

We use a multinomial mode choice model which is sensitive to costs, travel time, age, trip purpose and availability of cars and public transport tickets[6]. Every generated trip consists of an ID of the person, start point, end point, start time, mode of transport, car used if applicable, estimated arrival time, as well as type and length of activity. The acceptance of a day plan depends on the absolute deviation A between the simulated total travel time and the originally reported total travel time. That means day plans that are 10 minutes shorter than the reported day plans have the same acceptance than plans that are 10 minutes longer than the reported ones. This strategy enables the location choice to choose destinations based on the desired travel time, e.g. a special restaurant far away or a very local shop, if time is running short. The acceptance B is calculated by an EVA1-function[15] with parameters E=7, F=5 and turning point G= 0.5 (see Equation 1)

$$B = \frac{1}{(1+A)^{\left(\frac{E}{1+e^{(F-A\cdot F/G)}}\right)}} \tag{1}$$

Additionally, the costs of the day plan are allowed to exceed the average mobility budget only by a reasonable amount of 50%. The demand is calibrated by limiting the search radius for possible destinations to meet the reported mode shares of the SrV2008.

Table 1: Population of Berlin 2010

Berlin 2010	Number
Persons	3,322,985
Households	1,937,355
Cars	1,185,293
Bikes	2,459,009

The trips obtained are imported into the traffic flow model SUMO, which forms a subset of the DTA models. In its mesoscopic variant, this model simulates the traffic flow using a queue-based approach[3]. The streets are modelled as segments with a transit time and a storage capacity for cars. Both ends of a segment have a limiting input and output rate. Street junctions are modelled as nodes where several segments are connected. The storage capacity is derived from lane and length information. The transit time and I/O-rates are calculated from observed junctions. The resulting speeds and traffic volumes are validated by data from existing traffic counting systems and floating car data from local taxi drivers[4]. The traffic is assigned to the network by a non-iterative algorithm which adapts the edge travel times online. After mapping the whole traffic through the network, a matrix containing the travel times from all possible origins to all possible destinations is generated with respect to the simulated network speeds. Additionally, the deviation of the planned and the actual travel times for all mapped trips is calculated to check if the system converges.

The generated travel time matrix is fed back into TAPAS and the demand is recalculated based on this matrix (see Fig. 2). However, a damping factor of 70% with respect to the last iteration is introduced to minimize oscillation effects on the travel times (tt) from location i to location j (see Equation 2). This iteration is currently done for a fixed number of cycles.

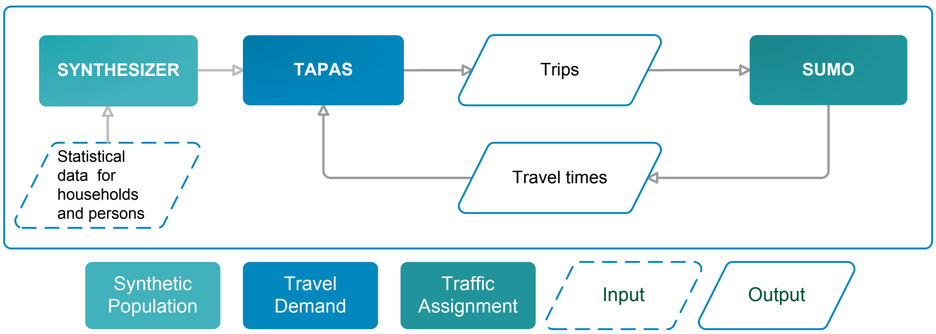

Fig. 2: TAPAS-SUMO Interaction

We test this approach on a reference case which replicates the year 2010. It generates approximately 11 million trips for the city of Berlin, of which approximately 2,6 million are performed by car. Modal shifts are calculated for every iteration. Furthermore, the trip lengths for each mode are given.

$$tt_{n+1}^{ij} = 0.7tt_{n-1}^{ij} + 0.3tt_{n}^{ii} \quad (2)$$

4. Results

The modal split values of the five iterations are shown in Table 2. The mode share of car trips drops by 2.5% from iteration 1 to iteration 2. The modal shift seems to be equally distributed to the remaining modes walking, cycling or using public transport. After the first iteration, only slight changes in the mode share can be observed.

Table 2: Modal split

Mode	SrV2008	Iteration 1	Iteration 2	Iteration 3	Iteration 4	Iteration 5
Walk	28.1%	26.2%	27.4%	27.3%	27.5%	27.7%
Bike	12.5%	11.3%	11.8%	11.8%	11.9%	11.8%
Car	31.5%	33.2%	30.7%	30.3%	30.2%	30.1%
Public transport	27.9%	29.4%	30.1%	30.5%	30.3%	30.3%
Abs. Dev. from SrV2008		6.3%	4.5%	5.3%	4.9%	4.9%

Initially, the shares of car trips and public transport trips are slightly overestimated. After every iteration, the mode shift due to the feedback of travel times improves the mode share for car, cycling and walking, while the deviation for public transport increases. Unfortunately, we lack valid GTFS data from the year 2008, so we used data from 2013. Between 2008 and 2013, however, a new central subway line was introduced and a major traffic hub in the east of the city was modernized. We assume that the overestimation of public transport is mainly due to these net effects. The absolute deviation of the mode shares is given in the last row. It decreased for all iterations after the first, but shows mixed tendencies.

The average trip lengths in meters per mode are shown in Table 3. The lengths of car trips drop by 310 meters from the first iteration to the second, which is a reduction of 4%. The trip length of public transport increases by 80 metres, which is a relative increase of 1%. All other modes show no significant change. The following iterations show only little changes compared to the first iteration. However, we see a general tendency of decreasing car trip lengths and increasing public transport trip lengths. Hence, the changed travel times result in a modal shift and a change in location choice at the same time.

Table 3: Average trip lengths in meters

Mode	Iteration 1	Iteration 2	Iteration 3	Iteration 4	Iteration 5
Walk	1962	1966	1969	1967	1966
Bike	6133	6127	6149	6137	6137
Car	7680	7368	7334	7311	7311
Public transport	8790	8870	8891	8861	8884

The average travel time of the simulated modes are shown in Table 4. Only the car-based modes show a change in travel times, while all other modes remain constant. The average car trip duration increases by 2.5 minutes or 11.3% after the first iteration and continues to increase slightly with each iteration. The technique to compute the initial travel time matrix for car described above underestimates the required travel times. The traffic flow detects these deviations, the travel demand reacts and the travel times remain constant after the third iteration.

Table 4: Average trip time in minutes

Mode	Iteration 1	Iteration 2	Iteration 3	Iteration 4	Iteration 5
Walk	29.6	29.7	29.7	29.7	29.6
Bike	26.3	26.3	26.4	26.3	26.2
Car	19.6	22.1	22.7	22.7	22.8
Public transport	42.5	42.6	42.7	42.6	42.6
Total	29.7	30.9	31.1	31.1	31.1

We analyzed the changes in the travel time matrix by building a histogram of the time deviations for all relations. In Fig. 3, the x-axis shows the distributions of the travel time differences between two subsequent iterations for all origin-destination relations in minutes. The y-axis displays the relative amount of relations. Since we display the change of two iterations, we calculated an additional traffic flow result to check the changes for the 5th iteration.

The differences between the first and the second iteration reach from –1 to 20 minutes, with a peak at 5 minutes. The distribution is very wide and the maximum peak has only a share of 12.8%. Comparing iterations two and three shows much less deviation. About 45.0% of all travel times show a deviation of less than one minute. All following iterations show almost no deviation from the third: 96.6% have a deviation of less than one minute. The system remains stable and equilibrium is reached after the third iteration.

The computing time for a single iteration was 4 hours for travel demand and 18 hours for the traffic flow on an Intel Xeon Processor with 16 cores, 32 threads at 3.4GHz and 64GB of RAM.

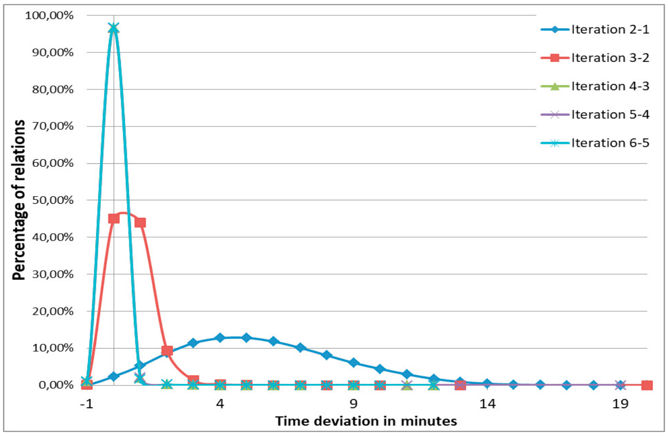

Fig. 3: Time deviations of the car travel time matrix over different iterations

5. Discussion

The results show that the travel demand computed by the agent-based demand model TAPAS quickly adapts to the new travel times generated by the traffic flow simulation SUMO. After three iterations, there is no significant change in the travel times and an equilibrium is reached which takes mode choice, location choice and traffic congestions into account. This yields a more realistic microscopic traffic simulation than models where the demand is fixed or only start times are shifted to avoid extreme congestions. What is more, the mode shares of the travel demand improve compared to the reported values of the SrV2008. The travel times for car trips increase compared to the initial run, which causes a mode shift to the alternative modes and also reduces the accessibility of certain areas. This effect results in choosing other destinations near-by to the actual position of the person and car trips become slightly shorter. This behavior is more realistic than trying to reach a location in a congested area by any means. At the moment, we only use one travel time matrix per day neglecting different travel times during peak hours. The approach shows fast convergence and we want to extend the model to include different time matrices over the day.

However, this fully integrated simulation model can optimize daily activities by multiple means: activity choice, location choice, mode choice and route choice. Partly integrated simulation models cannot optimize the entire set of choices. The proposed approach separates the complex route choice from the travel demand, which enables the two models to focus on their respective challenging tasks. The feedback allows interaction between them, which enables the travel demand model to take the time deviations into account when the daily activity plans are set up. As a result, the trip chains remain valid and subsequent activities on a complex route are less affected by time shifts due to dense traffic situations.

6. Conclusion

In this paper we presented a fully integrated simulation of ABM travel demand modelling with a mesoscopic traffic flow model for a large city with more than 3 million inhabitants. We showed that equilibrium between these two models can easily be reached within a few iterations. Changes in travel times result in changes in trip planning, for example by means of mode and location choice. Furthermore, the travel demand becomes more consistent because the planned trip times differ only slightly from the performed ones, which leads to feasible trip chains. The errors from inaccurate travel times do not propagate throughout the day plan, which enables the travel demand to assess the proposed plan correctly. This, in turn, enables the integrated model to show realistic results in a changed simulation setup where travel demand changes for multiple reasons such as demographic change, new infrastructure or changed pricing.

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